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RESEARCH ARTICLE

Managing risk and uncertainty in systematic conservation planning with insufficient information

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Abstract

1. Recent advances in systematic conservation planning make use of modern portfolio theory (MPT)—a framework to construct and select optimal allocation of assets—to address the challenges posed by climate change uncertainty. However, these methods are difficult to implement for fine-scale conservation planning when the information on future climate scenarios is insufficient. Insufficient information makes the estimators of the key inputs in the optimisation procedure unreliable leading to technical problems for the construction of optimal asset allocation.
2. We identify three statistical methods—constant correlation model, the Ledoit–Wolf approach and the weighted non-negative least-squares approach—that can overcome the lack of sufficient information and enable the use of MPT for fine-scale conservation planning.
3. We illustrate the use of the three methods for identifying efficient portfolio allocation strategies, that is, strategies that give minimum amount of risk for a chosen level of return or maximum return for a chosen level of risk, using case studies of wetland conservation planning in North America and coastal conservation planning in Australia. We compare conservation planning strategies with complete information using standard portfolio theory and with insufficient information using the three methods to highlight their advantages and disadvantages. We find the Ledoit–Wolf and weighted non-negative least-squares approaches perform well and can identify risk-return outcomes that are close to those identified with complete information.
4. The methods presented in this study broaden the range of cases where the application of MPT is possible in conservation planning to enhance its uptake and lead to more efficient allocation of conservation resources.

KEYWORDS

climate risk, diversification, insufficient information, natural resource management, portfolio theory, systematic conservation planning, uncertainty

1 | INTRODUCTION

Systematic conservation planning is a formal approach for identifying efficient spatial conservation actions and priorities for biodiversity conservation and is widely used around the world (Margules & Pressey, 2000; McIntosh et al., 2017). Yet, climate change uncertainty creates new challenges for systematic conservation planning (Heller & Zavaleta, 2009; Lawler, 2009; Walther et al., 2002). Standard approaches to conservation planning do not typically integrate objectives for risk that arise from future climate uncertainty, but new methods have recently been developed to incorporate climate uncertainties into the conservation planning paradigm. Several studies assess climate change risk for individual planning units, but do not consider the joint probability distributions across planning units that affects the overall risk of the conservation portfolio. Climate change often produces spatially variable impacts within and across different emission scenarios that strongly affect the co-variance in returns between planning units, in addition to the expected return and variance of individual planning units. This has major implications for the overall risk of the portfolio of conservation actions and therefore should be accounted for. Ando and Mallory (2012) develop a new risk management tool based on modern portfolio theory (MPT) that enables policy makers and conservation agents to use information about spatial co-variances in future ecological conditions to efficiently allocate conservation and environmental management investments across space. However, conservation planning at finer spatial scales cannot be implemented using the basic MPT framework in the absence of information on a large number of climate scenarios. This lack of sufficient information makes the estimators of the key inputs in the optimisation procedure unreliable leading to technical problems for the construction of optimal asset allocation. We explore the use of several statistical methods to develop spatially optimal disaggregated conservation investment strategies using data from only a small number of climate change forecasts.

Previous studies have used a variety of tools to account for climate change induced uncertainties in systematic conservation planning frameworks and illustrate methods for prioritising conservation areas (Carvalho et al., 2011; Hannah et al., 2007; Kujala et al., 2013; Moilanen et al., 2006; Polasky et al., 2011; Regan et al., 2005; Visconti & Joppa, 2015; Williams et al., 2005; Wintle et al., 2011). While some of these studies use information-gap theory to assess the robustness of existing or future conservation planning decisions (Moilanen et al., 2006; Regan et al., 2005), others use climate-envelope models (Hannah et al., 2007; Williams et al., 2005) or uncertainty analyses combined with return-on investment or simple cost-effectiveness measures (Carvalho et al., 2011; Wintle et al., 2011) to identify the most important areas for conservation under uncertainty. These studies provide methods to (a) quantify and account for uncertainties in species distribution models and (b) assess robustness of conservation planning decisions to underlying errors in data generation and model assumptions. However, they focus on planning unit by planning unit risk, rather than focusing on whole of portfolio risk. Some studies do recommend diversification, but do this by dividing investment among multiple sites using simple diversification algorithms (Anderson & Ferree, 2010; Beier & Brost, 2010)—that is, equal allocation of resources across all planning units. In contrast, MPT uses information about the joint probability distribution over all available climate scenarios and planning units to minimise overall portfolio risk. This method identifies a set of conservation portfolios that efficiently allocate conservation investments across planning units such that, for a given level of expected conservation outcomes (for a range of climate change predictions), the uncertainty in outcomes is minimised for the whole portfolio of investments; or alternately, for a given level of acceptable climate change uncertainty for the whole portfolio of investments, the expected conservation outcome is maximised.

Modern portfolio theory is a promising new approach to conservation planning that enables policy makers and conservation planners to efficiently diversify the risk of conservation outcome uncertainty across planning units such that expected negative environmental outcome in one planning unit is compensated by expected positive environmental outcome in other planning units. In an MPT framework, the risk of a portfolio of planning units selected to achieve a desired conservation outcome is based on the individual variances associated with each planning unit and the co-variances among the different planning units included in the portfolio. Thus MPT uses information on spatial co-variances in future ecological conditions to efficiently allocate conservation and environmental management resources across space, while managing risk explicitly (Ando & Mallory, 2012). The management of risk in this way can lead to substantially different spatial priorities depending on the risk preferences of the conservation planner. A conservation planner that wants to reduce the risk or uncertainty associated with a conservation outcome will have to target a lower level of expected conservation outcome; alternately, a conservation planner that has a higher risk preference can target a higher expected conservation outcome.

Modern portfolio theory has been applied to a variety of conservation planning problems to identify the most efficient allocation of conservation resources. These efficient allocations, or portfolios, form an efficient frontier and identify the best trade-offs between climate change risk and expected conservation outcomes. Many early applications of MPT to conservation problems focused on the protection of conservation assets such as species, populations and ecosystems to identify, but were not spatially explicit (Crowe & Parker, 2008; Figge, 2004; Koellner & Schmitz, 2006; Moore et al., 2010; Schindler et al., 2010). More recent studies use MPT to identify the optimal spatial allocation of conservation resources across spatially explicit planning units to manage climate change risk (Ando & Mallory, 2012; Mallory & Ando, 2014; Runting et al., 2018; Shah et al., 2017).

However, MPT can be information intensive because it requires estimates of the distribution and correlation structure of future risks. These information requirements can be particularly demanding for conservation settings with large number of planning units (Shah et al., 2017). For instance, simulating conservation outcomes for planning units under climate change usually relies on a limited

TABLE 1 Fundamental concepts in modern portfolio theory

Term	Definition
Portfolio	Collection of assets held by an investor
Modern portfolio theory	Framework to construct and select portfolios based on the expected performance of the investments and the risk appetite of the investor (Fabozzi et al., 2002)
Return	Relative change in the value of an asset
(Portfolio) weight	Proportion of the conservation budget that is allocated to an asset
Risk-return trade-off	Principle based on the idea that higher returns are associated with higher risk

set of climate scenarios generated from different general circulation models (GCMs) and future emissions trajectories for a range of climatic variables. Therefore, generating and verifying potentially thousands of distributions for each planning unit is likely to be beyond the computational capacity, expertise and time available to most conservation planners.

When the conservation decision variables are continuous (e.g. optimally allocating investment in conservation actions across different locations), a key limitation of MPT is that, when information is available for N scenarios or climate forecasts of different possible conservation outcomes, it is only possible to determine how to optimally allocate conservation resources among at most $N - 1$ planning units (Ando & Mallory, 2012). If the number of planning units is greater than the number of available future scenarios, we have a case of insufficient information and the variance–covariance matrix (VCM) among planning units is not of full rank as required to solve for the optimal solution (Shah et al., 2017). In particular, this insufficient information leads to a rank-deficient sample VCM of the expected returns associated with the spatial planning units and the inverse of the VCM cannot be calculated. This is a significant methodological challenge given that the number of future climate scenarios is usually limited, while conservation planning problems can often have hundreds, or even thousands, of planning units. For conservation planning with discrete decision settings (e.g. optimally choosing sites for protected areas), the problem of insufficient information is not as stringent, as shown in Runting et al. (2018). Discrete conservation prioritisation problems, such as identifying locations for protected areas, are commonplace (Margules & Pressey, 2000). Yet, conservation planning is now increasingly focused on more general problems that aim to identify where to invest resources in different actions, such as management activities or incentives, to achieve conservation outcomes (Crowe & Parker, 2008; Kaim et al., 2017; Marinoni et al., 2011). In these cases the true decision variables (i.e. how much to invest in an action) are often continuous, but can still involve a very large number of planning units. The problem of insufficient information therefore narrows the scope of using MPT for these more general problems under climate change.

Shah et al. (2017) identify an iterative approach to address the problem of insufficient information for continuous decision settings and illustrate its use for conservation planning across 25 subregions in the Prairie Pothole Region (PPR) of the United States with only six climate scenarios. However, that approach requires several iterations and the results can depend on how the conservation features are initially grouped into broader categories. Here we review and identify robust and efficient methods for conservation planning under climate change risk for scenarios with insufficient information. We draw on studies from the finance literature that have suggested several VCM estimation strategies to efficiently use MPT to derive optimal portfolio allocations even with insufficient information (Elton & Gruber, 1973; Haskell & Hanson, 1981; Ledoit & Wolf, 2003, 2004). We use three estimation strategies: the constant correlation model (CCM; Elton & Gruber, 1973), the Ledoit and Wolf (LW) shrinkage estimator (Ledoit & Wolf, 2003) and the weighted non-negative least-squares (WNNLS) estimator (Haskell & Hanson, 1981), and illustrate their application to derive optimal conservation portfolio allocations for two conservation planning case studies from North America and Australia. We evaluate the different estimation strategies by comparing the resulting portfolios to the 'true' optimal portfolios obtained using all available information. For the case study from North America we also assess the performance of the estimators using short-term forecasts.

2 | MATERIALS AND METHODS

We consider a conservation planner's problem of allocating limited conservation resources across N planning units to achieve a target conservation outcome and to efficiently manage climate change risk to acceptable levels using a continuous decision MPT framework. Since key concepts in MPT, which are common in finance literature, may not be familiar to conservation studies practitioners, we provide relevant definitions in Table 1.

2.1 | The MPT decision problem

Consider a vector, say $\boldsymbol{r}$, of N future returns, which are random because of the uncertainties of future outcomes. Mathematically the random vector $\boldsymbol{r}$ is defined as:

$$\boldsymbol{r} = \begin{pmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{pmatrix},$$

where r_i is the return of asset i. In our empirical study we treat planning units as 'assets' and conservation benefits as 'returns'. Note that while returns in finance are based on the monetary value of the assets (stocks, bonds, derivatives, etc.), the definition of conservation benefits depends on the conservation study under investigation—we provide two examples in Sections 3.1 and 3.2.

We assume that $\boldsymbol{r}$ has existing mean vector $\boldsymbol{\mu}$ and VCM $\boldsymbol{\Sigma}$ defined as:

$$\boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_N \end{pmatrix} \quad \text{and} \quad \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \cdots & \sigma_N^2 \end{pmatrix},$$

where μ_i is the expected value of r_i, σ_i^2 is the variance of r_i and $\sigma_{ij} = \sigma_{ji}$ is the covariance between returns i and j for $i, j = 1, 2, \ldots, N$. In simple words, the mean vector specifies the expectations, while the VCM specifies the variances and the covariances of the returns.

Following standard MPT (Markowitz, 1952) we define the conservation agent's optimisation problem as,

$$\min_w \boldsymbol{w}'\boldsymbol{\Sigma}\boldsymbol{w} \tag{1}$$

under the constraints

$$\boldsymbol{w}'\boldsymbol{1} = 1, \tag{2}$$

$$\boldsymbol{w}'\boldsymbol{\mu} = \mu_p, \tag{3}$$

where $\boldsymbol{w}$ is a vector of portfolio weights (i.e. the proportion of the conservation budget) to be allocated across N planning units, of the (conservation) returns, $\boldsymbol{1}$ is a conformable vector of ones, μ_p is the desired target portfolio return. The $N \times 1$ vector $\boldsymbol{\mu}$ and the $N \times N$ matrix $\boldsymbol{\Sigma}$ are defined as above. Note that $\boldsymbol{w}'$ is the transposed vector $\boldsymbol{w}$. The constraint (2), that is, the weights sum to unity, ensures that the full amount set aside for conservation planning is invested and the constraint (3) ensures that the expected value of the portfolio is set to the desired target return. The latter is related to the risk preferences of the investor as higher returns are associated with higher risk. If the conservation agent seeks the least risky portfolio (i.e. the minimum possible portfolio variance), then the target function is minimised only under constraint (2) and the resulting portfolio is labelled as the global minimum variance portfolio.

An analytic solution to the optimisation problem in (1) exists (see e.g. Campbell et al., 1996), which requires the inverse of $\boldsymbol{\Sigma}$.

Since $\boldsymbol{\Sigma}$ is not known, an estimate such as the sample VCM, for example, $\boldsymbol{S}$, is used instead. Thus, it is a requirement that the sample VCM is invertible. A necessary condition for an invertible VCM is that it is of full rank and this condition is satisfied as long as $N < T$, that is, the number of planning units is less than the number of climate scenarios under consideration. To eliminate solutions with negative weights, we add additional non-negativity constraints to the optimisation problem in (1):

$$w_i \geq 0, \quad \text{for} \quad i = 1, \ldots, N$$

When non-equality constraints are added (1) cannot be solved analytically and quadratic programming (QP) algorithms are used instead.

2.2 | MPT under insufficient information

When the number of climate change scenarios is larger than the number of planning units, that is, $T > N$, $\boldsymbol{S}$ is of full rank and invertible and standard QP methods, such as Goldfarb–Idnani algorithm (Goldfarb & Idnani, 1982) can be used. The Goldfarb–Idnani algorithm is easily run for example in the statistical software R (R Core Team, 2019) using the command `solve.QP` from the package `quadprog` (Turlach & Weingessel, 2019).

However, when the number of planning units is larger than the number of climate change scenarios, that is, $N > T$, $\boldsymbol{S}$ is rank deficient (see Ledoit & Wolf, 2003) and therefore non-invertible. In this case the Goldfarb–Idnani algorithm, which requires the quadratic matrix in the optimisation problem (1) to be of full rank, breaks down.

To overcome the problem of insufficient information, we suggest three alternative approaches: CCM, LW shrinkage estimator and the WNNLS algorithm.

2.2.1 | The constant correlation model estimator

The CCM estimator assumes that the pair-wise correlations between the conservation benefits of any two planning units across the different climate scenarios are the same, although the variances of the conservation benefits associated with individual planning units are allowed to vary. Thus, the CCM imposes a strict structure on the VCM which reduces the number of parameters to be estimated to $N + 1$ (N variances and 1 correlation) compared to $\frac{N(N+1)}{2}$ parameters in the sample VCM without the CCM.

The CCM estimator is of full rank and invertible even when $T < N$. However, the CCM implies that the observed pair-wise differences in correlations are not statistically significant. This is a strong assumption which may only hold in very few conservation settings. The estimation procedure for the VCM using the CCM estimator is as follows:

1. Calculate the sample correlations between all possible pairs of returns (conservation benefits).
2. Calculate the mean of the resulting pairs.
3. Calculate the sample variances for each of the N assets.
4. Calculate the estimated covariances, say $\hat{\sigma}_{ij}$, for each possible pair using the equation:

$$\hat{\sigma}_{ij} = \hat{\rho}\sqrt{\hat{\sigma}_i^2}\sqrt{\hat{\sigma}_j^2},$$

where $\hat{\rho}$ is the correlation estimated in step 2, $\hat{\sigma}_i^2$ and $\hat{\sigma}_j^2$ are the estimated variances in step 3.

2.2.2 | Ledoit–Wolf shrinkage estimator

Ledoit and Wolf (2003, 2004) develop an estimator that is specifically designed to deal with the problem of insufficient information. The LW estimator aims to combine an estimator that relies on a structure (such as the CCM estimator) and an estimator that relies only on the data (such as the sample VCM). The LW estimator is defined as:

$$\widehat{\boldsymbol{\Sigma}}_{\mathrm{LW}} := \widehat{\delta}\boldsymbol{F} + (1-\widehat{\delta})\boldsymbol{S}, \tag{4}$$

where $\boldsymbol{F}$ is the structured VCM, also called the shrinkage target, and $\widehat{\delta}$ is an estimated shrinkage constant, which lies between 0 and 1. We assume that the shrinkage target is the CCM; however, there are also other alternatives (e.g. the identity matrix). Equation (4) implies that the LW estimator is a weighted average between the structured and the sample VCM. Ledoit and Wolf (2003) show that the LW estimator is invertible and well-conditioned.

The shrinkage constant δ is chosen such that it minimises the expected distance between the shrinkage estimator and the true VCM (see Ledoit & Wolf, 2004 for details on its estimation). We note here that the calculations are straightforward to code in R. The shrinkage constant δ is a function of the sum of the asymptotic variances of the entries in the sample VCM, the sum of the asymptotic co-variances of the entries in the structured estimator with the entries in the sample VCM and the mis-specification of the structured estimator, which is the difference between the structured VCM and the true VCM. Ledoit and Wolf (2004) provide additional details on how $\widehat{\delta}$ is calculated.

2.2.3 | The weighted non-negative least-squares algorithm

The CCM and LW estimators can be used in the Goldfarb–Idnani algorithm. An alternate approach is to use a QP algorithm that finds a solution to (1) under constraints (2) and (3) for rank-deficient estimates of $\boldsymbol{\Sigma}$. One such algorithm is the WNNLS algorithm introduced in Haskell and Hanson (1981) and implemented in R within the `MSCMT` package (Becker & Klößner, 2018).

The WNNLS algorithm is our preferred choice because it is more accurate in producing the optimal solution and computationally faster, (see figure 1 and table 1 on p. 9 in Becker & Klößner, 2018 and the accompanying discussion) compared to alternative QP algorithms such as ipop or LowRankQ (implemented in R with the function `ipop` in the package `kernlab` (Karatzoglou et al., 2004) or with the function `LowRankQP` in the package `LowRankQP` (Ormerod & Wand, 2020). However, one drawback of the WNNLS algorithm is that currently there is no standard documentation for its use in R.

2.2.4 | The naive diversification strategy

We compare our results using the three estimators with a naive diversification strategy. The naive diversification strategy, also known as the $1/N$ strategy, assigns equal weights to all assets and therefore no estimation is required. It can be shown that it is the global minimum variance portfolio obtained from (1) when the assets are uncorrelated and have the same variance. The advantage of the naive diversification is that no estimation is required and can be preferred when the estimates of $\boldsymbol{\Sigma}$ are unreliable. This strategy is used as a benchmark in our study.

3 | EMPIRICAL CASE STUDIES

To demonstrate the advantages of the proposed estimators, we apply them to two distinct case studies. The first case study focuses on how to optimally allocate conservation resources in the PPR in North America (Shah et al., 2017). The second case study focuses on the problem of investing in sites for conserving coastal wetlands in Moreton Bay, Queensland, Australia (Runting et al., 2018).

3.1 | Prairie Pothole Region in North America

The PPR covers an area of 75,000 km^2 (see Figure 1) and is important for conservation of wetland ecosystem services such as carbon sequestration, floodwater storage, wildlife habitat, reduction in soil erosion, etc. (Gleason et al., 2008).

Shah et al. (2017) assume that the benefits of wetland conservation in the PPR are directly related to the cover-cycle index (CCI). The CCI is a measure of wetland habitat quality and wetland functional dynamics and Johnson et al. (2010) show that the CCI is highly correlated with biodiversity and general wetland quality. Shah et al. (2017) use iterative portfolio optimisation to determine the best conservation resource allocation strategy across 25 regions in the PPR when the number of climate scenarios is < 25. They compare these results with the optimal portfolio allocation strategy using the full dataset where 35 future regional climate scenarios ('observations') of CCI outcomes are available for $N = 25$ planning units ('assets'). The authors assume that all 35 scenarios are possible and that each scenario has an equal probability. The mean vector and the VCM of the conservation benefits are then the sample mean and the sample VCM over the full dataset.

For the PPR case study, we explore the two scenarios discussed in Shah et al. (2017): (a) the representative scenario and (b) the high-emission scenario. The 'representative scenario' is based on a sample of six observations that is representative for the entire population of 35 climate scenarios. The 'high-emission scenario' is based on a biased sample of six high greenhouse-gas-emission climate scenarios—see Shah et al. (2017) for details. In both cases the information is insufficient because $T = 6 < N$.

We use the following steps for the study design for the PPR:

1. Obtain the 'true' efficient frontier on a (σ, μ) diagram using the 'true' mean vector and VCM using full information.

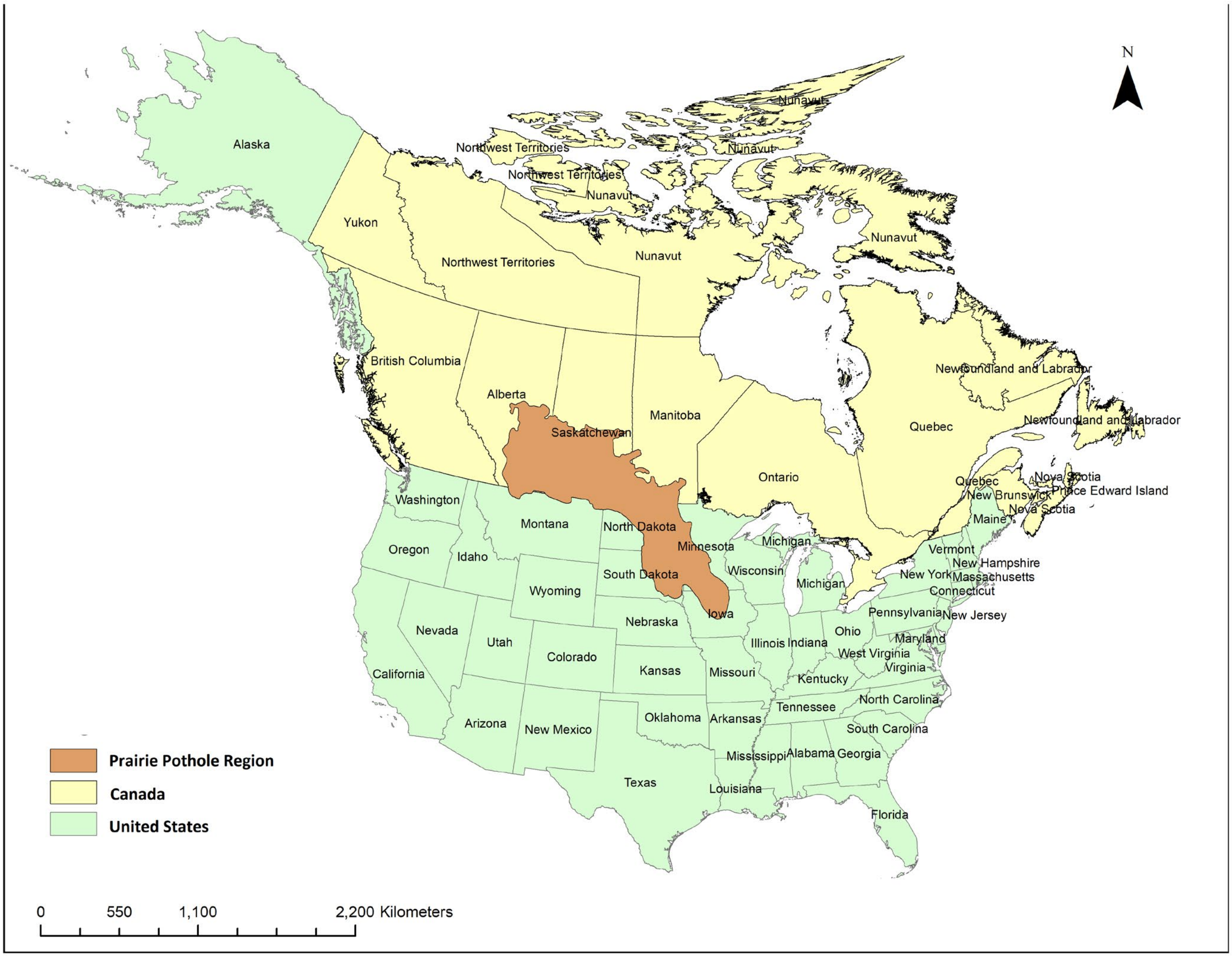

FIGURE 1 Map of the Prairie Pothole Region (PPR) in North America

2. For each case (representative and high emission) obtain the portfolios using the CCM, the LW and the WNNLS approaches. We choose 50 equally spaced target returns between the minimum and the maximum values in the 'true' mean vector.
3. Calculate the 'true' position on the (σ, μ) diagram for these portfolios using the 'true' mean vector and VCM of the assets.

This procedure is equivalent to comparing the out-of-sample performance of the different approaches measured by the mean and standard deviation of the portfolio returns when the number of draws from the population of scenarios is infinitely large.

3.2 | Coastal wetlands in Australia

Next we consider optimal conservation planning for coastal wetland conservation in Moreton Bay, Queensland, Australia discussed in Runting et al. (2018)—see Figure 2.

The distribution of coastal wetlands can be altered by sea-level rise, either by loss through continual inundation, or shifting landward in the absence of physical barriers. Similar to Runting et al. (2018) we use the area of wetlands (primarily mangroves, salt marsh and melaleuca) simulated to occur in the year 2100 using the sea level affecting marshes model (SLAMM; Clough et al., 2012) as a measure of ecological benefits associated with each planning unit. SLAMM is a mathematical tool that can be used to simulate wetland transitions and shoreline modifications under sea level rise (Runting et al., 2017). We assume a linear relationship between conservation benefits and the area under conservation. We then derive benefit to cost ratio for each planning unit by dividing the expected area of wetland in 2100 for each planning unit by the cost (in millions) of conserving that planning unit as an estimate of the marginal benefit per dollar spent on conservation management in each planning. To estimate the cost of each planning unit, we use the unimproved land value per planning unit with a 20,000 AUD transaction cost per property (Adams et al., 2011; DERM, 2013). For the Moreton Bay case study, we focus on two scenarios: Moreton Scenario A and Moreton Scenario B.

For Moreton Scenario A, we consider the first 1,000 planning units, that is, $N = 1{,}000$, after removing planning units which either (a) had perfectly correlated conservation benefits with the

FIGURE 2 Map of Moreton Bay, Queensland, Australia. The black square indicates the study site

conservation benefits of another planning unit; (b) had conservation benefits with zero variance (i.e. no change in all scenarios); or (c) were planning units that were already protected. For the selected planning units, we calculate the marginal benefits and the benefit to cost ratio, with the unimproved land value representing costs (Hinchliffe & Queensland, 2009). For the full dataset we use $T = 1{,}428$, thus we have complete information such that $T > N$.

Moreton Scenario A enables us to work with a large-scale optimisation problem, similar to the financial problems for which the estimators were developed. The evaluation procedure is similar to the one described in Section 3.1. We then considered one insufficient information case, in which we randomly choose $T = 300$ scenarios.

In Moreton Scenario B, we address the problem of high spatial correlation among the planning units. While this is rarely the case in financial applications, this phenomenon is realistic for fine-scale conservation planning as neighbouring planning units are likely to have highly correlated forecasts. Our aim for the second scenario is to compare the performance of the three strategies on a reduced dataset, which excludes highly correlated assets. For the Moreton Scenario B, we can compare the performance of the three strategies—CMM, LW approach and WNNLS approach—on a reduced dataset, where only a few correlations are > 0.88. More precisely, we consider a portfolio of $N = 52$ planning units and draw a random sample of size $T = 25$ scenarios (such that $T < N$).

4 | RESULTS

4.1 | Prairie Pothole Region in North America

4.1.1 | Representative scenario

The results for the representative scenario (based on a sample of six observations that is representative for the entire population of 35 climate scenarios) from the PPR are shown in Figure 3. We also include the results from the naive diversification strategy ($1/N$ rule) and the iterative portfolio selection approach, labelled the 'envelope' approach, used in Shah et al. (2017).

Figure 3 illustrates that it is possible to obtain a wider range of 'efficient' portfolios based on the CCM, the LW and the WNNLS approach compared to the iterative portfolio selection approach at almost no computational costs. The model mis-specification based on the CCM seems to be substantial as this is the worst performing estimation procedure. This is not surprising as the 'true' correlations range between -0.938 and 0.997—thus, the assumption of a constant correlation is not appropriate in this case. Nevertheless, the CCM results are better than the naive diversification.

The LW estimator provides satisfying results. The portfolios are close to the 'true' efficient frontier and for σ lower than 0.06, they lie above the portfolios obtained from the iterative portfolio selection approach. Moreover, portfolios with lower variance are feasible with this estimation technique.

The WNNLS performs the best in the representative case—the portfolios obtained are very close to the true efficient frontier. For smaller variances, the LW and the WNNLS approach clearly outperform the iterative approach (i.e. 'envelope') used in Shah et al. (2017).

4.1.2 | High-emission scenario

The results for the high-emission scenario for the PPR are shown in Figure 4.

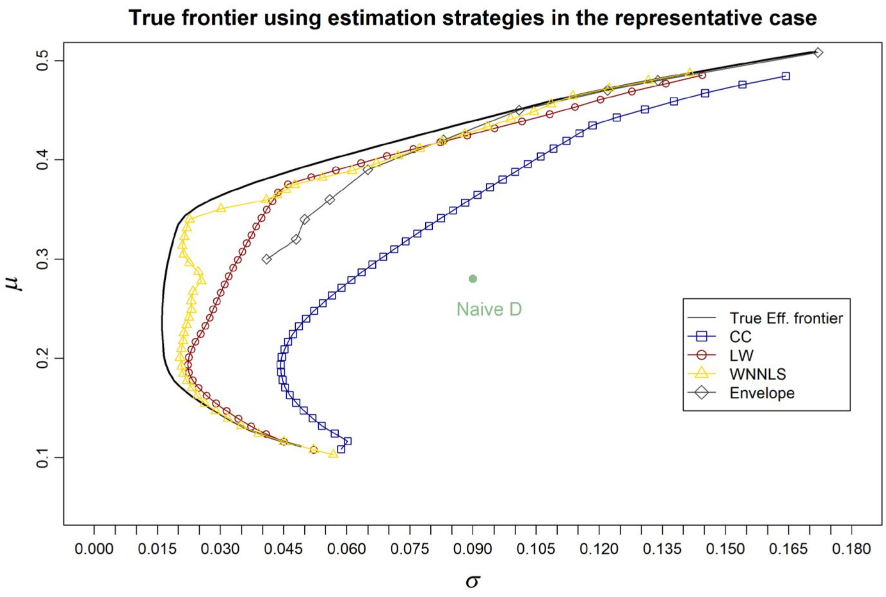

FIGURE 3 Prairie Pothole Region study: 'True' efficient frontier and positions of portfolios obtained using different estimation techniques in the representative scenario. CC stands for constant correlation (model), LW for Ledoit–Wolf (estimator), WNNLS for weighted non-negative least squares (algorithm). The green dot is the position of the portfolio obtained using naive diversification (Naive D)

For the high-emission scenario, the comparative advantages of the LW and the WNNLS approaches are lost. This is not surprising because the high-emission case uses a biased sample of the true values for the CCI and therefore violates the assumption that the sample VCM is a consistent estimator. We find that in this case the sample VCM severely underestimates (in absolute value) the 'true' VCM, which is to be expected as there is less variation in the sample than in the population. The CCM estimator does not provide satisfactory results either although the portfolios based on the CCM have lower variance (but also lower expected return) compared to other strategies.

The iterative portfolio selection approach does not seem to be affected by the bias in the estimated sample VCM and recommends portfolios close to the 'true' efficient frontier. However, this strategy provides only a few feasible efficient portfolios.

Finally, to test the robustness of the results, we compare the short-term out-of-sample performance of the three strategies—LW, CCM and WNNLS estimators with the iterative approach used in Shah et al. (2017). For this purpose, we use the portfolio weights calculated by the different approaches when a representative sample is available and set the target return to be 0.36, which is close to the middle of the range of mean asset returns and is also included in the iterative approach in Shah et al. (2017). We consider two cases. In the first case, we assume that the six scenarios from the high-emission scenario occur in the next six time periods. This enables us to compare the performance of the portfolios if a high-emission period follows the investment decision. In the second case, we randomly choose six of the scenarios not included in the representative scenario. This enables us to compare the performance of the portfolios if

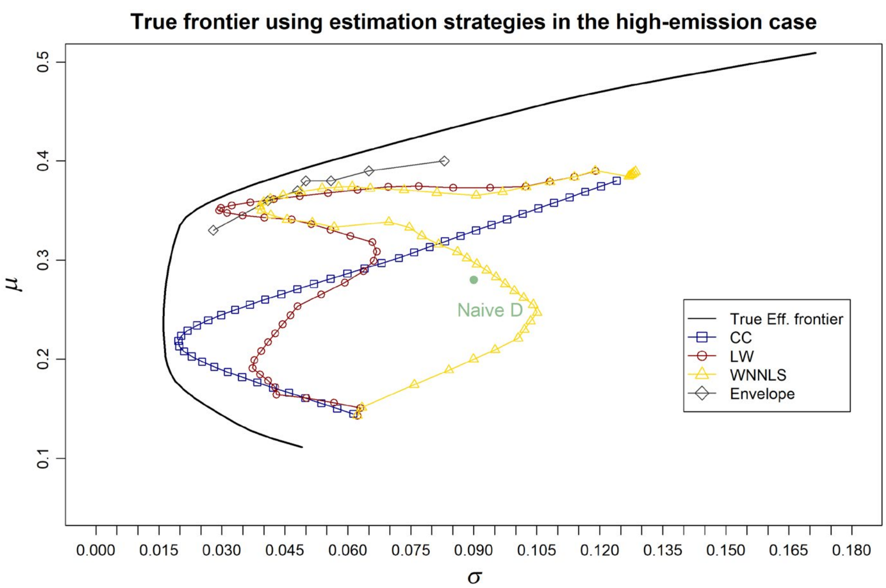

FIGURE 4 Prairie Pothole Region study: 'True' efficient frontier and positions of portfolios obtained using different estimation techniques in the high-emission case. CC stands for constant correlation (model), LW for Ledoit-Wolf (estimator), WNNLS for weighted non-negative least squares (algorithm). The green dot is the position of the portfolio obtained using naive diversification (Naive D)

scenarios occur that were not taken into account in the estimation but do not follow any particular pattern. In each case we calculate the mean and the standard deviation (*SD*) of out-of-sample conservation benefits based on the six portfolios. The results are shown in Table 2.

In the high emission future scenario, MPT with the LW and WNNLS estimators recommend mean portfolio returns that are close to the target return. The uncertainty associated with the WNNLS portfolio returns is substantially smaller than that associated with the other approaches. In the random future scenario, the LW approach provides the smallest variance for the portfolio return. Overall both LW and WNNLS estimators provide satisfying results in the context of out-of-sample forecasts.

4.2 | Coastal wetlands in Australia

4.2.1 | Moreton Scenario A

For the coastal wetlands case study, the results for Moreton Scenario A are shown in Figure 5. We obtain portfolio weights using the CCM and the WNNLS estimators for the insufficient information case. The LW estimator cannot be applied for the Moreton Scenario A because $\hat{\delta}$ is negative. This is likely due to the fact that a large number of planning units are nearly perfectly correlated. Ledoit and Wolf (2004) indicate that this could happen and suggest truncating δ to zero. This effectively means that the LW estimator delivers the sample VCM and is therefore identical to the WNNLS approach in this case. The naive diversification results in a portfolio with a very high variance; thus, we chose to exclude it from this analysis.

As seen in Figure 5, both the WNNLS and CCM estimators perform relatively well for the continuous decision setting. Both the efficient frontiers, based on the WNNLS and CCM estimators, are very close to the 'true' efficient frontier (i.e. the efficient frontier estimated using the continuous decision setting with complete information).

4.2.2 | Moreton Scenario B

The results for Moreton Scenario B are shown in Figure 6. For this scenario, it is possible to derive the LW estimator (in addition to the WNNLS and CCM estimators) since $\hat{\delta} \approx 0.017 > 0$. By design we included only a few planning units with correlations > 0.88.

For Moreton Scenario B, the CCM estimator performs better than the LW and WNNLS estimators. Thus, assuming a constant correlation among the 52 planning units provides risk-return trade-offs that are better than those recommended by the LW and WNNLS estimators. This may be due to the substantial sampling variation as we randomly chose 25 planning units out of 1,428 planning units.

5 | DISCUSSION

Information regarding climate uncertainty and environmental outcomes is often limited and difficult to acquire. This makes it challenging to implement standard conservation planning using MPT for a large number of planning units. Even when such information can be gathered, extensive and expensive data collection and ecological modelling efforts are required which can substantially increase conservation planning costs. We identify and compare three different estimators that can enable a conservation agent to conduct portfolio allocation among a large number of planning units with limited climate change information. These approaches are popular choices in financial applications of portfolio selection but have not been applied to conservation settings. In the absence of the required number of climate change scenarios, the estimators identified in this study perform better than or similar to the methods developed by Shah et al. (2017). However, these estimators have the added advantage that they provide a wider range of desired portfolio returns and are less computationally intensive.

We demonstrate the merits of two particular approaches—the LW estimator, which is a weighted average of a structured and an unstructured VCM estimator, and the WNNLS estimator, which is based on a QP procedure for optimising the target function in portfolio selection, under a rank-deficient VCM of the returns. We find that both estimators perform relatively well with incomplete information and can provide risk-return trade-offs that are similar to the best possible risk-return trade-offs as determined by the 'true' efficient frontier based on sufficient information. We also demonstrate the use of a third estimator, CCM, which is simple and easy to understand and implement. The CCM estimator can be used when there is a narrow range of correlations among the planning units.

The LW estimator is our preferred choice for conservation planning problems that include a large number of planning units. First, it can be easily interpreted as a balanced estimator of the variance–covariance matrix that is based on a combination of prior beliefs and the actual data. Second, it is straightforward to code in a statistical software such as R. Third, it is computationally efficient. In our two example case studies we demonstrated that it produces portfolios close to the 'true' efficient frontier. Furthermore, it performed well in short-term out-of-sample forecasts as its conservation benefits had lower risk than competitive approaches. However, the LW estimator can lead to less optimal results when the available sample of climate scenarios is biased or when there is high spatial correlation between the planning units. In such cases, an alternative is the CCM estimator. The WNNLS estimator also performs relatively well and is found to be the best option when conservation returns are highly correlated. One of the disadvantages of this method is that currently it is not widely accessible due to limited documentation on its implementation in R. We conclude that ultimately it is the choice of the conservation planner which of the suggested methods to use—a decision that will depend on the context of the conservation study in question, for which we provide some guidance here.

In this study, we focus on conservation planning problems where the decision choice is assumed to be continuous. Discretising conservation planning problems that have continuous decision variables and solving numerically may help overcome the problem of insufficient information (Runting et al., 2018). Future work should explore the performance of the estimators used here, which allow for continuous decision variables, relative to the discretisation approach. Some conservation planning problems may actually require the use of a combination of continuous and discrete decision MPT analyses to arrive at the most optimal risk-return trade-offs where different actions may be either truly discrete or truly continuous (e.g. discrete decisions for property purchases and continuous decisions for investment in management actions). Whether actions are discrete or continuous may also depend on the scale of the planning decisions. For example, broad scale allocation of conservation funds is continuous in nature (Sánchez-Fernández et al., 2018), whereas finer scale decisions may be mixtures of discrete and continuous decisions. Fine-scale conservation planning decisions often involve allocating investments to smaller planning units that may not be as divisible as for larger planning units. Thus, conservation planning decisions at fine scales may be more appropriately formulated using a discrete decision variable. Poiani et al. (2000) illustrate that biodiversity, ecosystem services and species occur at a variety of geographic scales, ranging from regional and coarse scale to intermediate and local scales. Thus, planning at a single scale is rarely sufficient and conservation planners can benefit from a multi-scale approach. Tingley et al. (2014) indicate that such novel approaches that combine coarse- and fine-scale approaches for conservation planning, for example using coarse-filter approaches to identify priority areas at the regional level and then using fine-filter approaches to focus on species-specific conservation actions within each individual location, can better accommodate the conservation planning needs for a changing climate. A two-stage or nested MPT analyses where in the first stage, broad scale conservation planning is made using continuous MPT analyses and in the second stage, regional or sub-regional conservation planning is made using discrete MPT analyses, may be useful in such circumstances. Future research could assess the use of the three estimators for such two-stage MPT analyses.

TABLE 2 Comparison of the forecast short-term out-of-sample conservation benefits based on different portfolio optimisation approaches when the weights are calculated under the representative scenario and the target return is set to 0.36. 'High emission' and 'Random' refer to the out-of-sample scenarios. *SD* stands for standard deviation of the out-of-sample conservation benefits

	High emission		Random	
	Mean	*SD*	Mean	*SD*
LW	0.3449	0.0184	0.3375	0.0477
CCM	0.3185	0.0528	0.3113	0.0871
WNNLS	0.3493	0.0086	0.3433	0.0546
Iterative approach	0.3600	0.0410	0.3700	0.0650

Abbreviations: CCM, constant correlation model; LW, Ledoit and Wolf; WNNLS, weighted non-negative least-squares.

For simplicity, we assume a linear relationship between area under conservation and the conservation benefits accrued for each planning unit and no diminishing marginal returns in each planning unit. In reality, however, many conservation actions are likely to have diminishing marginal returns within each planning unit (Withey et al., 2012). For example, if the goal of conservation planning is to invest in protecting habitat to maximise the number of species conserved, we would expect the number of species conserved per unit area to be a monotonically decreasing function of the area protected if the number of species follows a typical species–area relationship. In this case the conservation returns in each unit area will diminish with increasing investment in protecting habitat. In such cases, the no diminishing marginal return assumption could lead to over investment in particular planning units that strongly exhibit diminishing returns. This issue of diminishing returns in MPT analyses is

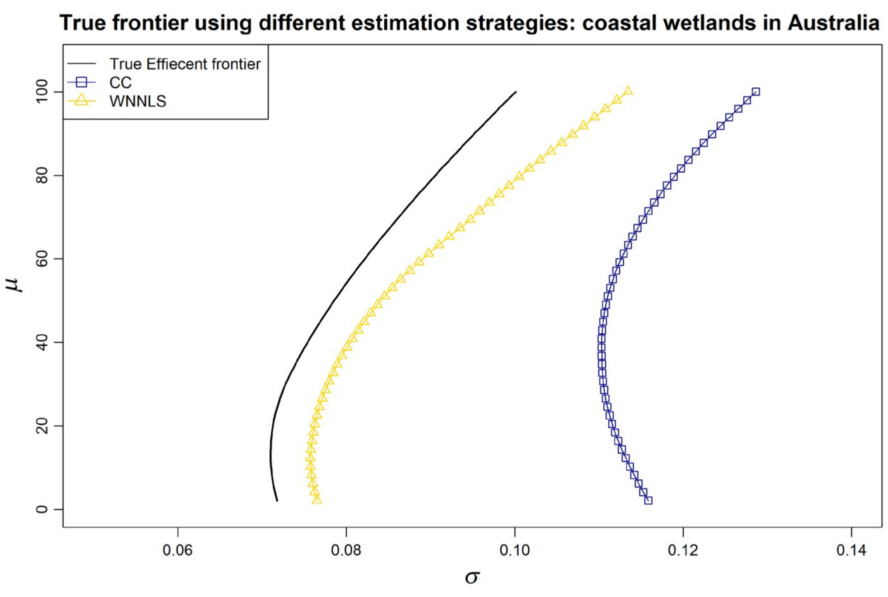

FIGURE 5 'True' efficient frontier and positions of portfolios obtained using different estimation techniques for the coastal wetlands case study. The estimating approaches are based on a sample of $T = 300$ scenarios for $N = 1{,}000$ parcels. The 'true' efficient frontier (solid line) is based on a sample of $T = 1{,}428$ scenarios for $N = 1{,}000$ parcels

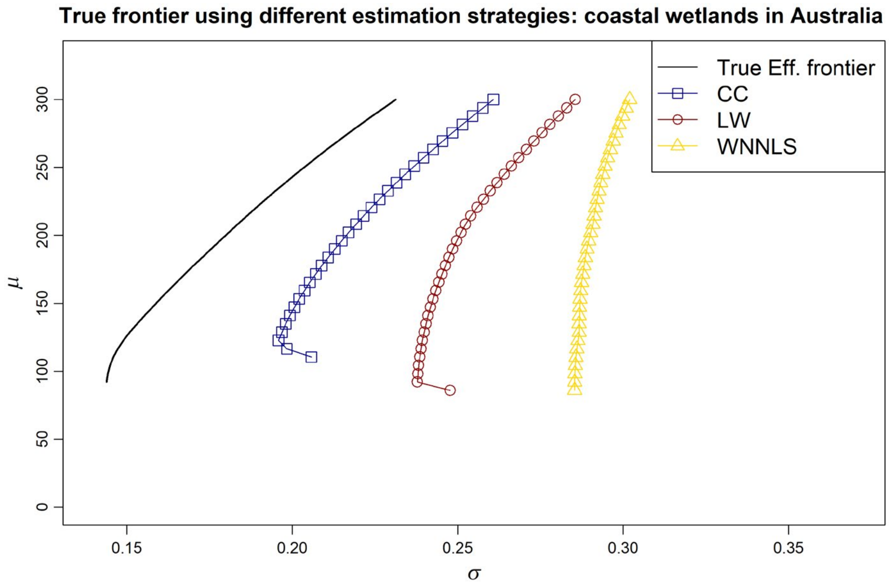

FIGURE 6 'True' efficient frontier and positions of portfolios obtained using different estimation techniques for the coastal wetland in Australia. The estimating approaches are based on a sample of $T = 25$ scenarios for $N = 52$ parcels

not of particular concern in the financial markets where linear benefit functions are appropriate. The development of approaches for finding solutions for MPT problems with nonlinear benefit functions is likely to be a key challenge for the further development of MPT to conservation planning problems. As part of this development, how the solutions to the insufficient information problem presented here perform will be essential. This will be especially relevant for conservation planning problems with a large number of planning units and the relationship between area under conservation and conservation benefits is nonlinear.

Modern portfolio theory has broad-based applications in ecological settings and is a useful tool to address a range of economic and ecological uncertainties that create conservation investment risks that may be correlated and affect the aggregate risk exposure of the conservation investment portfolio. However, the three statistical estimators identified in this study are designed to help in ecological settings where there is a problem of insufficient information. This is especially relevant for climate uncertainty because generating a large number of alternative climate scenarios is likely to be impractical because we often have to rely on the finite number of existing climate scenarios available. Even in cases where uncertainty other than climate change (e.g. ecological uncertainty) takes precedence and it may be feasible to collect more data, it is important to explore whether the conservation benefits from improved predictions will outweigh the costs of using more sophisticated models to gain the additional information. Previous studies have explored the trade-offs between the costs and benefits of using more sophisticated modelling techniques to collect additional data of future ecosystem responses to global change. Several studies show that the added benefits of collecting additional data do not always outweigh the costs involved in getting that data (Grantham et al., 2008; Runge et al., 2011; Williams et al., 2011). Alternately, other studies show that investment in more complex models and techniques to acquire detailed information can lead to better conservation outcomes (Runting et al., 2013).

6 | CONCLUSIONS

All three statistical estimators identified in this study can perform well compared to the full information MPT analyses in the presence of insufficient information and can lead to potential cost savings due to lower information requirements. Of the three estimators, LW estimator performed consistently well across the case studies considered in this paper and is our preferred estimator for determining the best risk-return trade-offs between conservation portfolio risk and conservation outcomes when the available number of predicted scenarios are insufficient. However, when the expected conservation outcomes across planning units are highly correlated, the WNNLS estimator tends to be the more reliable choice. The CCM estimator is our least preferred method but it is much easier to understand and implement and can provide relatively robust results when the range of correlations across planning units is narrow. Our study highlights methods to implement efficient spatial conservation planning in the face of conservation outcome uncertainty even when the data are inadequate. For conservation planning where resources are scarce and have to be divided between data collection and implementation activities, it is important to consider the novel approaches shown in this study.

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CONFLICT OF INTEREST

None of the authors have conflict of interest.

AUTHORS' CONTRIBUTIONS

V.P. wrote the manuscript, conducted the analysis and interpreted the results; P.S. wrote the manuscript and assisted with the interpretation of the results; J.R.R. assisted with the interpretation of the results and revised the manuscript; R.K.R. assisted with conducting the analysis and revised the manuscript.

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DATA AVAILABILITY STATEMENT

The data used in this paper are accessible on https://dataverse.harvard.edu/dataverse/managingrisk.

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